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MULTI-CRITERIA MODEL-DRIVEN FEATURE SELECTION USING FUZZY RULED CLASSIFICATION OF STAGES OF ANAESTHESIA

Christian Walther, Rudolf Baumgart-Schmitt*, Christoph Menz*, Daniel Trommer*, Maria Krautwald*, Klaus-Peter Sturm**, Uwe Jäger****

* Lab. Neuroinformatics, Faculty of Electrical Engineering, University of Applied Sciences Schmalkalden, Germany
** Department of Anaesthesia, Hospital of Schmalkalden, Germany
*** Medical practice of Zella-Mehlis, Germany

ABSTRACT

The optimal feature set to classify stages of anaesthesia by fuzzy rules should be identified. The one-channel frontal electroencephalogram (EEG) was measured on the forehead during operation. The feature set for the classification task was extracted on the basis of this one channel EEG. No vital data like heart rate or blood pressure are used. Data sets from 100 patients and operations were considered. Three different stages of anaesthesia are defined as light, normal and deep anaesthesia. The Strength Pareto Evolutionary Algorithm (SPEA) was applied to control the selection of features used by the fuzzy rules. This algorithm being available in the advanced second version (SPEA2) was adapted to the problem. The classification performance for each anaesthetic stage is described by the true-positive (sensitivity) and the false-positive (specificity) recognition of the epochs of all EEG data sets. By using three different anaesthetic stages six different criteria evaluate the feature selection and the corresponding fuzzy rules. Therefore a multi-criteria optimisation model is established. The analysis of the produced values for sensitivity and specificity results into an optimal estimation of feature sets which can be used by the fuzzy rules to classify the stages of anaesthesia. To reduce the dimensionality of the optimisation problem the parameters of the fuzzy sets and the general structures of the rules are invariable. Only the selection of the included fuzzy sets is optimized. This corresponds to the selection of the features to classify the anaesthesia stages.

Index Terms - Multi-objective, feature selection, fuzzy rules, EEG, anaesthesia, classification

1. INTRODUCTION

This paper describes problems of algorithmic and automatic electroencephalographic (EEG) analysis in anaesthesia [1,2,3]. To determine different stages of anaesthesia by means of the frontal one-channel EEG populations of fuzzy rules can be used. The rules use features based on the time and frequency space. The selection of these features can be handled as an optimisation problem. By using different criteria to estimate the performance of the fuzzy model a multi-criteria optimisation problem is defined. The fuzzy rules can be optimised using approaches of Evolutionary Algorithms (EA). With multiple criteria for performance estimation a Multi-objective Evolutionary Algorithm (MOEA) is advised. Different MOEAs were established within the last years [4,5]. For optimisation of the feature sets the second version of the Strength Pareto Evolutionary Algorithm (SPEA2) was selected.

2. METHODS AND MATERIALS

2.1. Database

The anaesthesia EEG of 100 patients was collected in the hospital of Schmalkalden (Germany) and in the medical practice for ambulant surgery in Zella-Mehlis (Germany). The EEG was sampled at 504 Hz and conducted from the forehead. So a one-channel EEG-signal was saved patient-specific for every operation and filtered (high-pass, low-pass, notch) before used for optimisation. The structure of the EEG signal changes during the procedure of anaesthesia. Both variances of amplitudes and frequencies can be observed. Table 1 lists a typical division of EEG-waves concerning their features in frequency range.

The EEG-signal-structure can be divided into three different main stages: “Light Anaesthesia”, “Anaesthesia” and “Deep Anaesthesia”. The main characteristics of each stage are listed in the tables 2-4 and are based on [6]. The EEG recordings were divided into epochs of ten seconds for optimisation of the fuzzy rules. For every epoch of the EEG features were calculated and saved with the corresponding visual rated classification performed by an expert. Using this data pool the generated fuzzy should be able to classify the different stages of anaesthesia (figure 1). Technical and biological artifacts were manually excluded.

Notation	Range
δ (delta)	>0 - <4 Hz
θ (theta)	4 - <8 Hz
α (alpha)	8 - < 14 Hz
β (beta)	14 - < 30 Hz
γ (gamma)	>= 30 Hz

Table 1 Division of EEG-waves concerning their frequency range [6].

Light Anaesthesia
- higher activity in the upper frequency range (β, γ), γ-activity is dominant
- highest values for all edge frequencies
- high values for Approximate Entropy [7]
- sleep spindles (13-17Hz) could be observed

Table 2 Defined main characteristics of the anaesthesia stage "Light Anaesthesia".

Anaesthesia
- higher activity in the lower frequency-range
- dominant activity in the δ-, θ- or α-range
- γ-activity is minor
- values of edge frequencies and Approximate Entropy [7] are lower

Table 3 Defined main characteristics of the anaesthesia stage "Anaesthesia".

Deep Anaesthesia
- the structure of the eeg-signals contains burst-suppression-patterns
- Burst-Suppression-Ratio is high valued

Table 4 Defined main characteristics of the anaesthesia stage "Deep Anaesthesia".

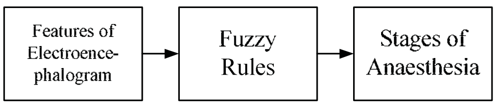

Figure 1 Approach of classification. The features of the electroencephalogram are used by the fuzzy rules to determine different stages of anaesthesia.

2.2. Fuzzy Logic

A Mamdani fuzzy approach is used to classify the three different stages of anaesthesia. The input variables are based on features of the EEG. 53 linguistic input variables are defined and to every variable three different fuzzy sets were advised. For each fuzzy set of the input variables a gaussian membership-function was chosen:

$$\mu(x,a,b) = e^{[-0.5*((x-a)/b)]}, \tag{1}$$

with *x* as normalised input value based on features of EEG and *a* and *b* as parameters of the gaussian membership-function. The parameters *a* and *b* were generally fixed and not allowed to be changed within the optimisation process. At least one linguistic output variable named *anaesthesia-stage* was defined providing three fuzzy sets "Light Anaesthesia", "Anaesthesia" and "Deep Anaesthesia". These fuzzy sets use a singleton membership-function. Within every generated set of fuzzy rules at least five rules for each stage of anaesthesia were allowed for optimisation. Fuzzy rules of the following sample structure should be optimised by the algorithm:

If "Feature 1" = *low* and "Feature 2" = *high*, then "Anaesthesia Stage" = *Deep Anaesthesia*.

The fuzzy operators which could be used were restricted to a simple maximum-operator within the linguistic input variables:

$$\mu(f_k) = \max\{\mu_l(f_k), \mu_m(f_k), \mu_h(f_k)\}, \tag{2}$$

with f_k as a measured value of EEG feature *k* and $\mu_l(f_k)$, $\mu_m(f_k)$, $\mu_h(f_k)$ as membership values of the linguistic terms *low*, *middle* and *high* of the input variable. The minimum-operator is used on the membership values to realise the fuzzy AND:

$$\mu_{Anaesthesia}(AS) = \min\{\mu(f_1),...,\mu(f_{53})\}, \tag{3}$$

with *AS* (Anaesthesia Stage) as defined linguistic output variable and $\mu_{Anaesthesia}(AS)$ as a resulting membership value of one rule for the linguistic term *Anaesthesia* based on the feature-specific membership values $\mu(f_1)$ to $\mu(f_{53})$. The aggregation and defuzzification of the resulting membership value is performed by the maximum operator.

2.3. Optimisation

The selection of features used by the fuzzy rules has to be optimised. Different criteria were used for fitness evaluation of the rules. This approach of optimisation is presented in figure 2. To optimise the selection of features the Strength Pareto Evolutionary Algorithm (SPEA2) in the second enhanced version was used [5]. The SPEA2 is a multi-objective Evolutionary Algorithm. The main intension is to find the Pareto set in the multicriteria space. For each stage of anaesthesia two criteria are defined. The first one is the true-positive ratio (sensitivity) of all as true classified epochs of the requested stage. The second criterion is defined as the false-positive ratio (specificity) of all false classified epochs in relation to all epochs of other stages of anaesthesia. These criteria are defined for all three stages (tables 2-4) which results in 6 different criteria used by the SPEA2. The procedure of the SPEA2 is presented in figure 3. The SPEA2 starts with a randomly initialised population of individuals. One individual is defined by the model description of the fuzzy rules and the performance of the rules measured by the criteria. The SPEA2 uses a principle of elite population which means that efficient individuals are able to survive until the general end of the optimisation algorithm. At first the so called SPEA-Strength is calculated for every individual of the working population. The Strength describes how many individuals are dominated by the observed one. The number of dominated individuals is advised as SPEA-Strength. In a second step the SPEA-Fitness is calculated for all individuals of the working population. The Fitness describes how many individuals are dominating the observed one. Therefore the SPEA-Strength of all dominating individuals is summarised as Fitness value and advised to the observed individual. This means high Fitness values imply a bad performance of a individual or fuzzy model.

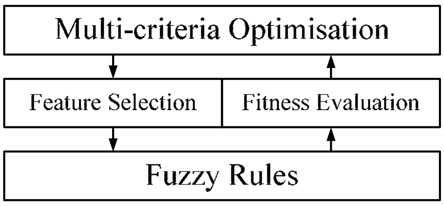

Figure 2 Approach of optimisation. The fitness of the fuzzy rules is based on the selected feature-space. The used Multi-criteria optimisation algorithm estimates the optimal feature combination.

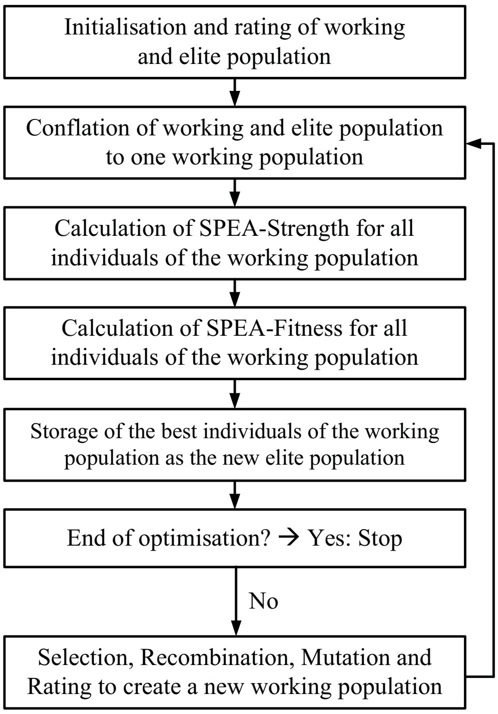

Figure 3 Strength Pareto Evolutionary Algorithm 2. The elite population contains the best individuals. The working population contains all individuals or child individuals only.

3. RESULTS

The optimal feature set was found for every patient and operation. The criteria of sensitivity and specificity were used for every anaesthesia stage within the SPEA2. So every individual of the evolutionary process represents the performance of a feature set in concordance with the model of the fuzzy rule set. For every data recording there were selected the best 24 individuals. By using recordings from 100 different patients and operations there were optimised 2400 fuzzy rule sets. The median values for all rules and stages of sensitivity and specificity are 71.6% and 90.0%. To evaluate the optimal feature selection the structure of all generated fuzzy rules was analysed. The tables 5-7 are presenting the resulting usage of the features of the individuals within the defined rectangle for every stage of anaesthesia. For the detection of the deepest stage of anaesthesia the feature space was manually restricted to special features of Burst-Suppression recognition. Overall there were provided 53 different features for the optimisation. The percentage values of the tables 5 and 6 imply a summarised usage of the first ten features of over 50%. An additional interesting result is that roundabout the half of the features were not used by the fuzzy rules and have an usage value of nearly 0%.

Light Anaesthesia
- SEF95 (spectral edge frequency): 5.82%
- δ-activity: 5.71%
- summarised activity (>4 to 11 Hz): 5.58%
- summarised activity (>11 to 14 Hz): 5.58%
- index of maximum value (>0 to 30 Hz): 5.43%
- PowerFastSlow [8]: 5.33%
- θ-activity: 5.30%
- index of maximum value (>0 to 4 Hz): 5.30%
- index of maximum value (8 to 14 Hz): 5.22%
- SynchFastSlow [8]: 5.18%

Table 5 Features used by the fuzzy rules for detection of the anaesthesia stage "Light Anaesthesia". The percentage values imply the usage of the feature related to all EEG recordings. The first most often used 10 features are listed.

Anaesthesia
- θ-activity: 5.70%
- index of maximum value (>0 to 30 Hz): 5.62%
- β-activity: 5.54%
- SynchFastSlow [8]: 5.50%
- index of maximum value (30 to 64 Hz): 5.38%
- index of maximum value (14 to 30 Hz): 5.36%
- summarised activity (>4 to 11 Hz): 5.35%
- γ-activity: 5.29%
- summarised activity (>11 to 14 Hz): 5.26%
- index of maximum value (>0 to 4 Hz): 5.24%

Table 6 Features used by the fuzzy rules for detection of the anaesthesia stage "Anaesthesia". The percentage values imply the usage of the feature related to all EEG recordings. The first most often used 10 features are listed.

Deep Anaesthesia
- Burst-Suppression-Detect 2 [9]: 26.06%
- Standard Deviation of Approximate Entropy [7]: 25.37%
- Suppression-Ratio: 24.65%
- Burst-Suppression-Detect 1 [9]: 23.92%

Table 7 Features used by the fuzzy rules for detection of the anaesthesia stage "Deep Anaesthesia". The percentage values imply the usage of the feature related to all EEG recordings

4. INTERPRETATION

The resulting feature selection which is presented in the tables 5 to 7 corresponds to the definitions of the stages of anaesthesia which are described in the tables 2 to 4. The resulting feature selection offers an interesting view onto the final feature set used by the fuzzy rules. For the detection of the stage "Light Anaesthesia" the δ-activity is for example primarily used by the fuzzy rules in opposition to the visual rating by the expert. Additionally the reduced and resulting feature set can be used as an optimal selection for a classification algorithm processed within an embedded solution. To increase the performance of the fuzzy rules an optimisation of the fuzzy operators could be implemented. Also the initial feature space could be reduced regarding to the results of this paper.

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